ROBUST HIERARCHICAL DATA FUSION FOR SENSOR NETWORKS

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ABSTRACT

The Smart Highway project, run by the South Korean government, is intended to improve the flow of traffic, convenience, and safety at high speeds of over 160 kilometers per hour. In order to achieve this goal, a large amount of information needs to be collected, including road conditions, environment, vehicle status, driver conditions, and other useful data. To this end, large-scale sensor networks can be an appropriate solution since they were designed for precisely this purpose. Recent advances in sensor network technology have enabled the management and monitoring of large-scale tasks, such as the road surface temperature monitoring system in a highway. In this paper, we consider the estimation and fusion problems in large-scale sensor networks for the smart highway system. For the arbitrary topology of a large-scale sensor network, new hierarchical fusion architecture is proposed. To achieve robustness of the network against outliers or the failure of sensors, a robust cluster estimator is also proposed. Finally, for the communication channel between clusters and the fusion centre, we propose a robust fusion scheme which considers the non-Gaussian channel noise typical in communication systems.

1. INTRODUCTION

A Smart Highway is a future high-speed road designed to reduce accident rates and create an intelligent and convenient environment for drivers by providing road, vehicle, environmental, and human information related to driving. This information will allow drivers to be more aware of the current conditions, thus improving safety and the overall driving experience. Many countries in the world have invested aggressively in the field of intelligent transportation system research, including South Korea. The South Korean government plans to construct a smart highway system with traffic speeds reaching over 160 Km/h, while guaranteeing minimal accident rates.

For a smart highway to function properly, it is necessary to collect and make available data regarding traffic flow, traffic control, accidental circumstances, road conditions, conditions of drivers and cars, and other environmental factors. This data is important in determining the circumstances which can cause accidents and to provide drivers with a more convenient and safer ambiance. Gathering and transforming this data into useful information also requires the integration of the smart highway system with information technology. In this regard, a large-scale sensor network provides a well-suited solution for this purpose.

The monitoring of road surface conditions is of paramount importance in a smart highway system. In particular, road surface temperatures need to be closely monitored because they can fluctuate significantly depending on the time of day, extent of cloud cover, sub-surface conditions (e.g. frost penetration, moisture presence and thermal retention properties) and type of road surface. Thus, a variety of sensors and equipment has been developed to both measure and monitor road and weather conditions. This equipment provides not only valuable information on road temperatures, but also on wet/dry status, the freeze point of the solution on the road, the presence and concentration of chemicals and subsurface temperatures. These sensors report the road surface as being wet, dry or frozen, along with reporting the road surface temperature. The sensors are embedded flush in the road and in the sub-surface in order to generate data that can be used to identify trends.

A common approach used in road surface sensors is the monitoring of road surface conductivity, which changes as road surface conditions change. Passive road sensors, for example, (see Figure 1)

sit in the road with no heat energy being transferred to or from the sensor. They attempt to measure the road surface conditions and residual salt using conductivity, capacitance, vibration, radar or some other method. Monitoring of the relative parameters of the road surface is equally important to improve the efficiency and effectiveness of winter maintenance operations and to better inform motorists of driving conditions. For example, the amount of highway salt used in de-icing roads is largely dependent upon the mass of snow or ice on the road surface and the pavement temperature. More accurate knowledge of the pavement surface temperature would assist in determining suitable salt application rates and could reduce salt waste. This would not only have fiscal and environmental benefits, but would also help to reduce structural degradation, such as chloride induced corrosion of reinforced concrete structures.

Figure 1. Two examples of road sensors.

Recent advances in large-scale sensor network technologies have enabled the deployment of a high number of sensors in the industrial environment. Each sensor consists of a small node capable of sensing, computing, and communication. Due to the limited processing capabilities of sensor nodes, however, the sensor readings are only minimally processed at the sensor network level. For further processing, the sensor data is transmitted through a multi-hop communication route to a centralized sensor database system. An important task of a sensor network is to be able to detect, track and classify objects. As objects move within the sensor field, they affect the observations of the nearby nodes. The key for collaboration across nodes, then, is to determine if there is a relationship between the observations of different nodes and to determine what this relationship is. These related observations are then used to form more accurate estimates for the existence, track and type of objects.

Graphical modeling techniques, such as Kalman filtering and hidden Markov models, have been employed very successfully in sensor networks [1], [2]. In terms of the network topology, our research focuses on large-scale sensor networks that lie within a two dimensional plane and a two-dimensional strip. The placement of sensors can vary significantly in different applications. In a “structured” sensor network application (e.g. a video surveillance system), sensors are placed at specified locations, while in an “unstructured” sensor network application (e.g. battlefield surveillance), sensors may be randomly dropped. In this work, we focus on the latter case where sensors are randomly placed in a field. These arbitrary networks are inherently robust and time efficient [3]–[5] and possess two important characteristics: (i) they are surprisingly fault tolerant against random node failures and (ii) they usually exhibit a *small-world* phenomenon [5], meaning that the average link length (in hops) scales logarithmically (or polylogarithmically) with the network size, resulting in considerable time efficiency. In addition, empirical studies [6] show that arbitrary topologies have a positive impact on the performance (fewer messages and smaller latency) of gossiping algorithms in static sensor networks. It is therefore conceivable that, in large-scale sensor networks, nodes can be grouped together to form arbitrary networks.

The deployment of a sensor network in a smart highway, however, presents several challenges. The first is the design and implementation of an arbitrary topology of a large-scale sensor network. This includes choosing both an arbitrary topology and an adequate set of communication protocols capable of providing the necessary autonomy. Secondly, the stringent restriction of sensor network nodes (non-Gaussian channel noise which is typical in communication systems) strongly influences the task of making decisions on the network architecture. Taking these premises as a starting point, we deal with the estimation and fusion problems in large-scale sensor networks with the aim of achieving optimal performance in the monitoring of road surface temperature. A road surface

temperature monitoring system model of a robust cluster estimator demonstrates the robustness of the network against outliers or the failure of sensors,

This paper is organized as follows. Section 2 sets out the problem in more detail. In Section 3, we propose the robust hierarchical estimate fusion algorithm within link failure between the sensors and cluster heads in sensor networks. Hence, fusion estimate in the fusion center is a linear combination of the fused estimates of each cluster head, and the fusion estimate of cluster heads is a linear combination of the local estimate. For this reason, the estimates fused in cluster heads are computed through a local filter in each sensor node. In Section 3, this local filter is introduced robust to measurement uncertainty. In Section 4, we present the simulation results from estimating the road surface temperature and some brief concluding remarks are provided in Section 5.

2. PROBLEM FORMULATION

Many advanced systems now make use of a large number of sensors in practical applications ranging from aerospace, robotics automation systems, to the monitoring and control of process plants. Recent developments in integrated sensor network systems have further motivated the search for decentralized signal processing algorithms. An important practical problem in the above systems is to find a fusion estimate to combine the information from various local estimates to produce a global (fusion) estimate. As previously stated, the goal of this research is to estimate and fuse road surface temperature data within sensor networks. In our research scenario, numerous temperature sensors are widely deployed throughout the smart highway to measure road surface temperature. To achieve global data fusion based on sensor measurements, a dynamic system is required and the temperature can be modeled as such with the measurement system representing temperature sensors. Hence, the following dynamic system can be briefly explained as [7]:

Nomenclature

$\mathbb{R}^{n}$:	Euclidean space of dimension $\mathbf{n}$
$\mathbb{R}^{n\times m}$:	Space of $n \times m$ real matrices
$\mathcal{N}\left(\bar{x},P\right)$:	Normal distribution with mean $\bar{x}$ and covariance matrix P
k :	Discrete time instance, $k = 0,1,2,...,\ \ t_k = k\Delta t$
Δt :	Sample time
$T_{s,k}$:	Road surface temperature at $t=t_k$
$T_{a,k}$:	Air temperature at $t=t_k$
D_k :	Dew point at $t=t_k$
h_k :	Relative humidity at $t=t_k$
$W_{a,k}$:	Average wind speed at $t=t_k$
$W_{m,k}$:	Maximum wind speed at $t=t_k$
v_k :	Environmental noise at $t=t_k$
$y_k^{(i)}$:	Temperature measurement from i^{th} sensor at $t=t_k$
$\xi_k^{(i)}$:	Measurement error in i^{th} sensor at $t=t_k$
$\theta^{(i)}$:	Uncertainty parameter for i^{th} sensor
N:	Total number of sensors in sensor network
L:	Number of clusters in sensor network

The dynamic system model for state vector x_k takes the following form:

$$x_k = \left[T_{s,k} \quad T_{a,k} \quad D_k \quad h_k \quad W_{a,k} \quad W_{m,k}\right]^T \tag{1}$$

$$x_{k+1} = F_k x_k + G_k v_k . \tag{2}$$

The multi-sensor measurement model including N sensors is given as

$$y_k^{(i)} = \theta^{(i)} H_k^{(i)} x_k + \xi_k^{(i)}, \quad i = 1, \dots, N, \quad k = 0, 1, 2, \dots, \tag{3}$$

where

$$x_k \in \mathbb{R}^{\mathbf{n}} \ (n=6), \quad y_k^{(i)} \in \mathbb{R}^{\mathbf{m_i}}, \quad i=1,\dots,N, \quad F_k \in \mathbb{R}^{n}, \quad v_k^{n} \in \mathbf{R},$$
$$w_k \in \mathbb{R}^{\mathbf{m_i}}, \quad G_k \in \mathbb{R}^{n\times r}, \quad H_k \in \mathbb{R}^{m_i}.$$

The environmental noise v_k and measurement errors $\xi_k^{(1)},\dots,\xi_k^{(N)}$ are uncorrelated white Gaussian noises, $v_k \in \mathbb{R}^r \sim \mathcal{N}(0,Q_k)$, $\xi_k^{(i)} \in \mathbb{R}^r \sim \mathcal{N}(0,R_k^{(i)})$, $i=1,\dots,N$. The initial state x_0 represents a normal distributed random vector, i.e., $x_0 \sim \mathcal{N}(\bar{x}_0, P_0)$. Note that all sensors (local filters) $y_k^{(1)},\dots,y_k^{(N)}$ are working on the same state vector x_k in (1), (2).

The unknown parameters $\theta^{(i)}$, $i=1,\dots,N$ take only two values

$$\theta^{(i)} = \begin{cases} \theta_1^{(i)}=0, & \text{"signal is absence"} \\ \theta_2^{(i)}=1, & \text{"signal is presence"} \end{cases} \tag{4}$$

A fundamental problem associated with such system (sensor network) is estimation of the current state x_k from the noisy measurements $\left\{y_k^{(i)}, \ i=1,\dots,N\right\}$.

In Sections 3, we propose robust hierarchical fusion filtering algorithm based on the adaptive Laniotis-Kalman filters (LKF's) [8], [9].

3. ROBUST HIERARCHICAL DATA FUSION WITHIN LINK FAILURE IN SENSOR NETWORKS

3.1 ARCHITECTURE FOR HIERARCHICAL FUSION FILTERING ALGORITHM

The hierarchical architecture selected for large scale sensor networks is shown in Figure 4a. Here, sensor nodes are connected to the nearest cluster and each cluster transmits the local fused estimate to the fusion center. The advantage of this topology is that it lessens the computation complexity of the decentralized data fusion algorithm. The sensor networks, based on the hierarchical architecture, consist of three layers. The first is a sensor system (sensor and node) which obtains the road surface temperature data (measurement value) and has the computational ability to estimate the state of the object based on the measurement value. The second layer, called the cluster head, obtains the information, which could be either a measurement value or an estimate and its covariance, from the first layer, and fuses all of the information. The third layer is the base station, or fusion center, that fuses all of the information previously fused from the clusters to compute global network estimate [10].

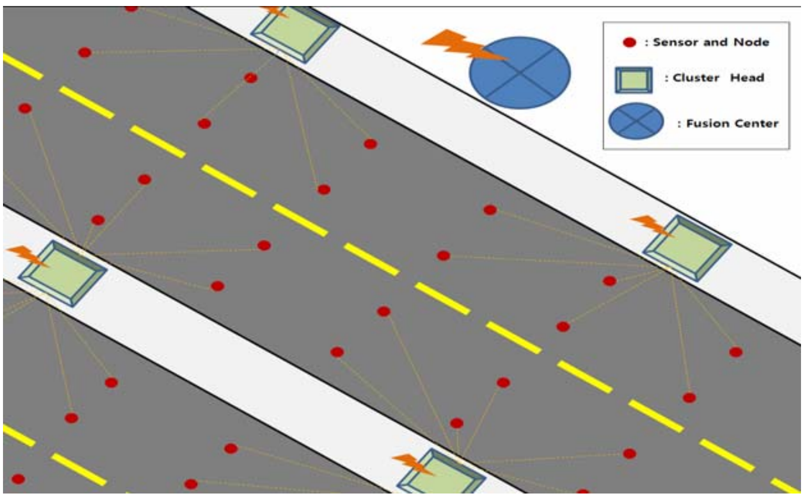

Figure 4a Hierarchical Data Fusion in Sensor Networks

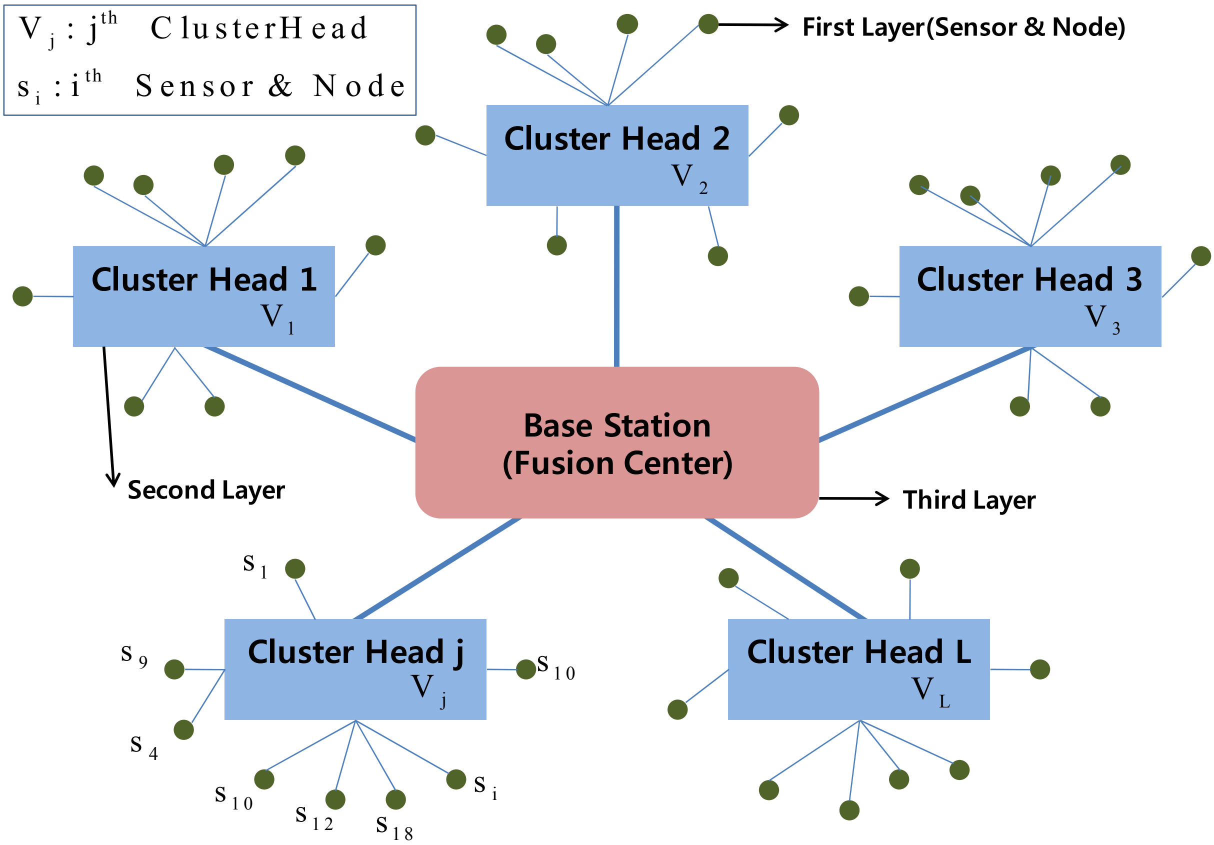

Figure 4b Hierarchical Data Fusion in Sensor Networks

3.2 ESTIMATION FUSION WITHIN LINK FAILURE BETWEEEN CLUSTER HEADS AND NODES

In most applications, the information used in sensor networks is converted to a form that provides the estimated state of the targeted objects. In numerous cases, especially in industrial applications, the information can be represented as means and variances which can be combined within the framework of Kalman-type filters. For instance, a decentralized sensor network used to determine the position of an unmanned aerial vehicle can combine the acceleration, fusing the estimates from nodes measuring the pressure of the engines with its angle sensors attached to each wing. If each independent node provides the mean and variance of the estimate from each sensor, fusing the estimates to obtain a better filtered estimate is not difficult [11].

The largest problem with decentralized data fusion in sensor networks is the effect of redundant information. To avoid this redundant information problem, covariance information must be maintained. Keeping consistent cross covariances in arbitrary decentralized networks, however, is not possible. The only reasonable way to achieve robustness and consistency in a general decentralized network is to exploit a data fusion mechanism such as Covariance Intersection (CI), that does not require independent assumptions [11].

In this Section, we propose a new robust hierarchical fusion filter for multisensor dynamic systems (1)-(4) for the sensor network in Figure 4b.

The proposed filter has three level hierarchical structures which includes 3 steps: *First step* (“Calculation of local Laniotis-Kalman estimates”), *Second step* (“Cluster’s Fusion of LKFs”) and *Third step* (“Global Network Fusion”). According to the three level structures we introduce the following notations:

- $\hat{x}_k^{(i)}$, $P_k^{(ii)}$: Optimal local LKF (estimate) of state x_k and corresponding error covariance based on i^{th} local sensor measurement (node) $y_k^{(i)}$, $i=1,\ldots,N$;
- $z_k^{(j)}$, $\Gamma_k^{(jj)}$: Fusion estimate and corresponding error covariance in j^{th} cluster head, $j=1,\ldots,L$.

- $\hat{x}_k^{gl}$, P_k^{gl}: Global network estimate of state x_k and corresponding global error covariance.

3.2.1 Local Laniotis-Kalman Filters (Estimates)

According to (2)-(4), we have N local dynamic subsystems with the same state vector x_k and local (individual) sensor measurement $y_k^{(i)}$ with uncertainty $\theta^{(i)}$:

$$
\begin{aligned}
&x_{k+1}=F_k x_k+G_k v_k, \quad k=0,1,2,...,\\
&y_k^{(i)}=\theta^{(i)}H_k^{(i)}x_k+w_k^{(i)}, \quad \theta^{(i)}=\left\{\theta_1^{(i)}\equiv 0, \quad \theta_2^{(i)}\equiv 1\right\},
\end{aligned} \tag{5}
$$

where the number i of a local subsystem is fixed.

To find local filter (estimate) $\hat{x}_k^{(i)}$ and its error covariance $P_k^{(ii)}$, we apply the LKF to the subsystem (5). According to the Lainiotis partition theorem the optimal mean-square state estimate $\hat{x}_k^{(i)}=\hat{x}_k^{opt}$ of x_k and the corresponding estimation error covariance $P_k^{(ii)}=P_k^{opt}$ are given by the weighted sums

$$
\begin{aligned}
\hat{x}_k^{(i)} &= p(\theta_1^{(i)}|y_k^{(i)})\hat{x}_k^{(i,1)}+p(\theta_2^{(i)}|y_k^{(i)})\hat{x}_k^{(i,2)},\\
P_k^{(ii)} &= p(\theta_1^{(i)}|y_k^{(i)})P_k^{(ii,1)}+p(\theta_2^{(i)}|y_k^{(i)})P_k^{(ii,2)},
\end{aligned} \tag{6}
$$

where $\hat{x}_k^{(i,1)}$, $\hat{x}_k^{(i,2)}$ and $P_k^{(ii,1)}$, $P_k^{(ii,2)}$ are the local estimates and corresponding error covariances, respectively, which are determined by the standard discrete Kalman filter equations matched to linear subsystem (5) at fixed $\theta^{(i)}=\theta_1^{(i)}$ or $\theta^{(i)}=\theta_2^{(i)}$ [12]:

$$
\begin{aligned}
&\hat{x}_k^{(i,h)}=F_k\hat{x}_{k-1}^{(i,h)}+K_k^{(i,h)}\left(y_k^{(i)}-\theta_h^{(i)}H_k^{(i)}\hat{x}_{k-1}^{(i,h)}\right), \quad \hat{x}_0^{(i,h)}=\overline{x}_0 \ ,\\
&M_k^{(i,h)}=F_kP_{k-1}^{(i,h)}F_k^T+G_kQ_kG_k^T, \quad P_0^{(i,h)}=P_0 \ ,\\
&K_k^{(i,h)}=\theta_h^{(i)}M_k^{(h)}H_k^{(i)^T}\left[\theta_h^{(i)^2}H_k^{(i)^T}M_k^{(h)}H_k^{(h)}+R_k^{(i)}\right]^{-1},\\
&P_k^{(i,h)}=\left(I_n-\theta_h^{(i)}K_k^{(i,h)}H_k^{(i)}\right)M_k^{(i,h)}, \qquad h=1,2 \ .
\end{aligned} \tag{7}
$$

Given $y_k^{(i)}$, the scalar weights $p\left(\theta_h^{(i)}\middle|y_k^{(i)}\right)$, $h=1,2$ in (6) represent *a posteriori* probabilities of $\theta_h^{(i)}$, $h=1,2$, which are described by the known recursive Bayesian formula [12].

So we have N local LKFs (estimates) $\hat{x}_k^{(i)}$, $i=1,...,N$ and corresponding error covariances $P_k^{(ii)}$, $i=1,...,N$. Next these values we use to calculate fusion estimate within each cluster.

3.2.2 Fusion Estimation in Cluster Heads

Let assume that the sensor network contains L cluster heads $V_1,...,V_L$ (see Fig. 4b). Consider j^{th} cluster head V_j and all sensors (nodes) $S_{i_1}, S_{i_2},...$ in its neighborhood. Let notation

$$
i\in V_j \tag{8}
$$

means that i^{th} node S_i is linked to the j^{th} cluster head and N_j represents total number of nodes which are linked to j^{th} cluster head. For example, $V_1=\{1,4,5,10\}$ means that the sensors S_1, S_4, S_5 and S_{10} are connected to first cluster head V_1, and $N_1=4$.

Then using the CI algorithm we fuse all local LKFs (see Figure. 4b)

$$\hat{x}_k^{(i)},\quad i\in V_j \tag{9}$$

within j^{th} cluster. The fusion cluster estimate $\hat{z}_k^{(j)}$ and its error covariance $\Gamma_k^{(jj)}$ take the form [13]

$$\hat{z}_k^{(j)}=\Gamma_k^{(jj)}\sum_{i\in V_j} w_k^{(i)}\left[P_k^{(ii)^{-1}}\hat{x}_k^{(i)}\right],\quad \Gamma_k^{(jj)-1}=\sum_{i\in V_j} w_k^{(i)}\, P_k^{(ii)^{-1}},\ j=1,...,L, \tag{10}$$

where the weights $w_k^{(i)},\ i\in V_j$ are calculated by

$$w_k^{(i)}=\frac{\det\left(\psi_k^{(j)}\right)-\det\left(\psi_k^{(j)}-P_k^{(ii)^{-1}}\right)+\det\left(P_k^{(ii)^{-1}}\right)}{N_j\times\det\left(\psi_k^{(j)}\right)+\sum\limits_{i\in V_j}\left[\det\left(P_k^{(ii)^{-1}}\right)-\det\left(\psi_k^{(j)}-P_k^{(ii)^{-1}}\right)\right]},$$
$$\psi_k^{(j)}=\sum_{i\in V_j}P_k^{(ii)^{-1}},\quad i\in V_j,\quad j=1,...,L. \tag{11}$$

Next using the L cluster's estimates and covariances $\hat{z}_k^{(j)}, \Gamma_k^{(jj)},\ j=1,...,L$, we get a final global network estimate $\hat{x}_k^{gl}$.

3.2.1 Global Network Estimate

As we see in Fig. 4b the base station globally fused all cluster's estimates $\hat{z}_k^{(j)},\ j=1,...,L$. Using the CI formulas (10), (11) we obtain global network estimate and its covariance

$$\left(P_k^{gl}\right)^{-1}\hat{x}_k^{gl}=\sum_{j=1}^{L}\tilde{w}_k^{(j)}\left[\Gamma_k^{(jj)^{-1}}\hat{z}_k^{(j)}\right],\ \left(P_k^{gl}\right)^{-1}=\sum_{j=1}^{L}\tilde{w}_k^{(j)}\,\Gamma_k^{(jj)^{-1}}, \tag{12}$$

where the weights are calculated by

$$\tilde{w}_k^{(j)}=\frac{\det\left(\Phi_k\right)-\det\left(\Phi_k-\Gamma_k^{(jj)^{-1}}\right)+\det\left(\Gamma_k^{(jj)^{-1}}\right)}{L\times\det\left(\Phi_k\right)+\sum\limits_{h=1}^{L}\left[\det\left(\Gamma_k^{(jj)^{-1}}\right)-\det\left(\Phi_k-\Gamma_k^{(jj)^{-1}}\right)\right]},$$
$$\Phi_k=\sum_{h=1}^{L}\Gamma_k^{(hh)^{-1}},\quad j=1,...,L. \tag{13}$$

Finally, the global network estimate takes the form

$$\hat{x}_k^{gl} = \left(\Gamma_k^{gl}\right)\sum_{j=1}^{L}\tilde{w}_k^{(j)}\,\Gamma_k^{(jj)^{-1}}\,\hat{z}_k^{(j)}. \tag{14}$$

The fusion formulas (10) and (12) are robust, since they can be corrected even if one of the local (filter) estimate ($\hat{x}_k^{(i)}$ or $\hat{z}_k^{(j)}$) diverges. In this case, the corresponding weight $w_k^{(i)}$ (or $\tilde{w}_k^{(i)}$) tends to zero, thereby indicating that the diverging estimate is discarded in the weighted sum (10) or (12).

4. SIMULATION

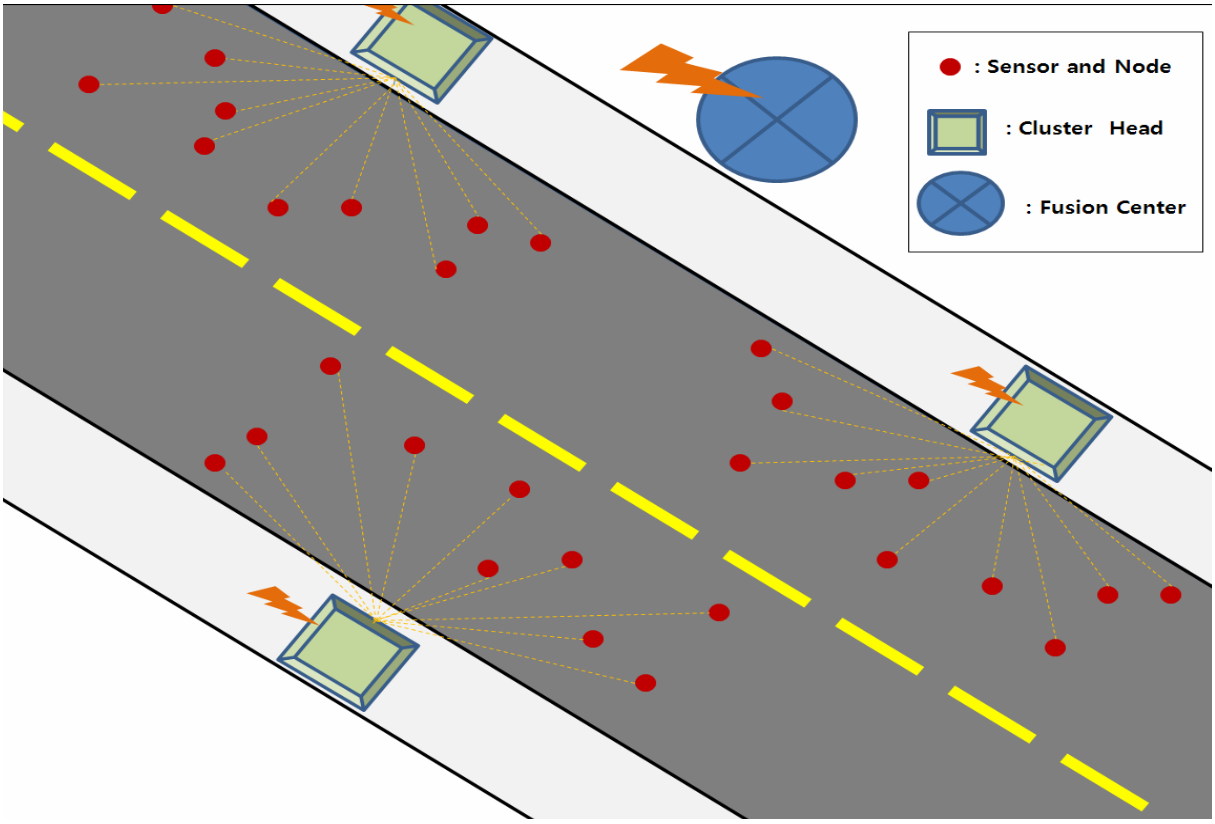

Figure 5 Simulation Description (30 sensors, 3culster heads, and one fusion center)

In this section, the previously explained algorithm is employed to globally estimate pavement temperature. To create a pavement temperature dynamic system model, linear regression analysis was used based on data for the metrological parameters including air temperature, dew point, relative humidity, average wind speed, and wind gust. These data sets were recorded for the dates of January 22 to February 4, 2007 [7]. Based on the data, the state parameter and measurement system was same as (1) and (2) in Section 2. All assumptions explained in Section 2 were also applied in this simulation. The time index "k" represents hours. The system model was constructed as

$$x_{k+1} = \begin{bmatrix} T_{s,k+1} \\ T_{a,k+1} \\ D_{k+1} \\ h_{k+1} \\ W_{a,k+1} \\ W_{m,k+1} \end{bmatrix} = \begin{bmatrix} 1.1091 & -0.4197 & 0.2644 & 0.0042 & -0.0223 & 0.0156 \\ 0.2204 & 0.5912 & 0.2 & 0.0012 & -0.0037 & 0.0076 \\ 0.1188 & -0.2199 & 1.0948 & 0.0002 & -0.0227 & 0.0105 \\ -0.2681 & 0.4987 & -0.2532 & 0.9989 & 0.011 & -0.0288 \\ 0.1904 & -0.1817 & -0.0028 & 0 & 0.3562 & 0.4448 \\ 0.2559 & -0.2002 & -0.0198 & 0.0072 & 0.1698 & 0.8046 \end{bmatrix} \begin{bmatrix} T_{s,k} \\ T_{a,k} \\ D_k \\ h_k \\ W_{a,k} \\ W_{m,k} \end{bmatrix} + \begin{bmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \\ g_5 \\ g_6 \end{bmatrix} v_k \tag{14}$$

The initial state mean value is

$$\bar{x}_0 = [-4 \quad -4 \quad -7.9 \quad 74 \quad 14.04 \quad 14.4]^T \quad , \quad P_0 = \text{diag}\,[18 \quad 19 \quad 24 \quad 68 \quad 50 \quad 78]$$

$$g_i = \text{const}, \;\; q = 1,\dots,6$$

$$y_k^{(i)} = \theta^{(i)} T_{s,k} + \xi_k^{(i)} = \theta^{(i)}[1\ 0\ 0\ 0\ 0\ 0]x_k + \xi_k^{(i)}, \qquad i = 1,\dots,30, \qquad k = 0,\,1,\,2,\,\dots\,,$$

As shown in Figure 5, the number of sensors is 30 and number of cluster is 3.
Set of sensors linked to 3 cluster heads are

$$V_1 = \{s_1, s_2, s_5, s_{10}, s_{12}, s_{15}, s_{18}, s_{21}, s_{22}, s_{28}\}$$
$$V_2 = \{s_3, s_4, s_7, s_{11}, s_{14}, s_{16}, s_{19}, s_{24}, s_{25}, s_{29}\}$$
$$V_3 = \{s_6, s_8, s_9, s_{13}, s_{17}, s_{20}, s_{23}, s_{26}, s_{27}, s_{30}\}$$

where $\theta^{(i)}$ takes two values $\theta_1^{(i)}=1$, $\theta_2^{(i)}=0$; scalar v_k and $\xi_k^{(i)}$ are uncorrelated zero-mean Gaussian white noises with intensity and Q and $\eta^{(i)}$, respectively. The initial state is subjected to $x_0 \sim N(\bar{x}_0, P_0)$. The prior probabilities were set to $p(\theta_1^{(i)}) = \frac{2}{3}, \;\; p(\theta_2^{(i)}) = \frac{1}{3}$. The value of system and measurement parameter were to set to: $Q = 5, \quad \eta^{(i)} = 0.5 \times i$.

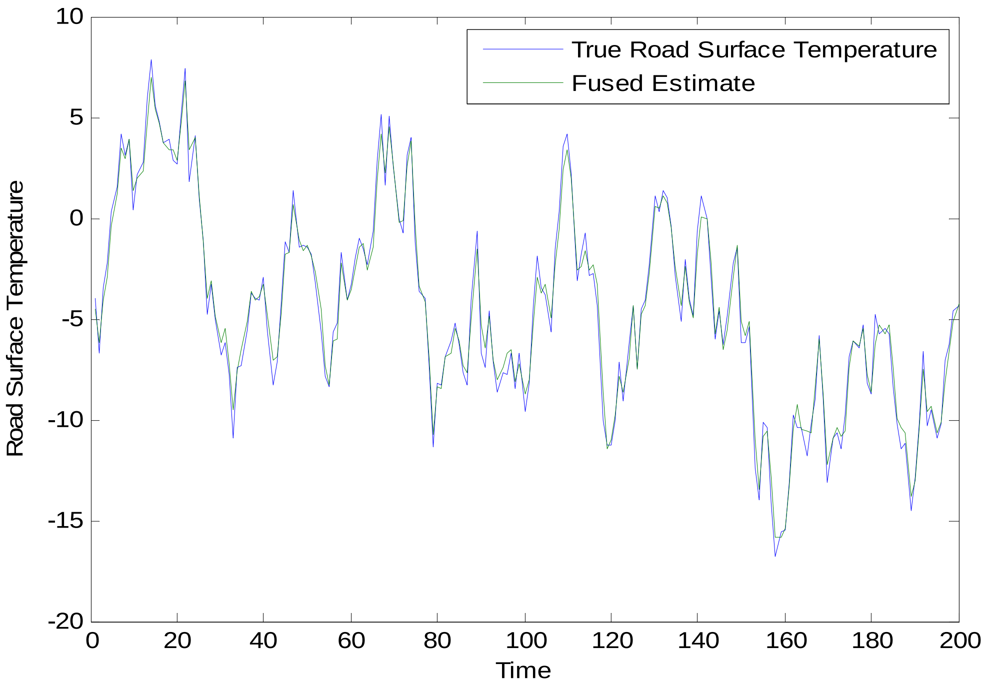

Figure 6. Real Road Surface Temperature and Globally Fused Estimate

In Figure 6, the global network estimate and true road surface temperature are compared. The result show that the estimate based on measurement uncertainty follows its true value in high accuracy. In Figure 7, the root mean square is shown to show the accuracy of proposed filter.

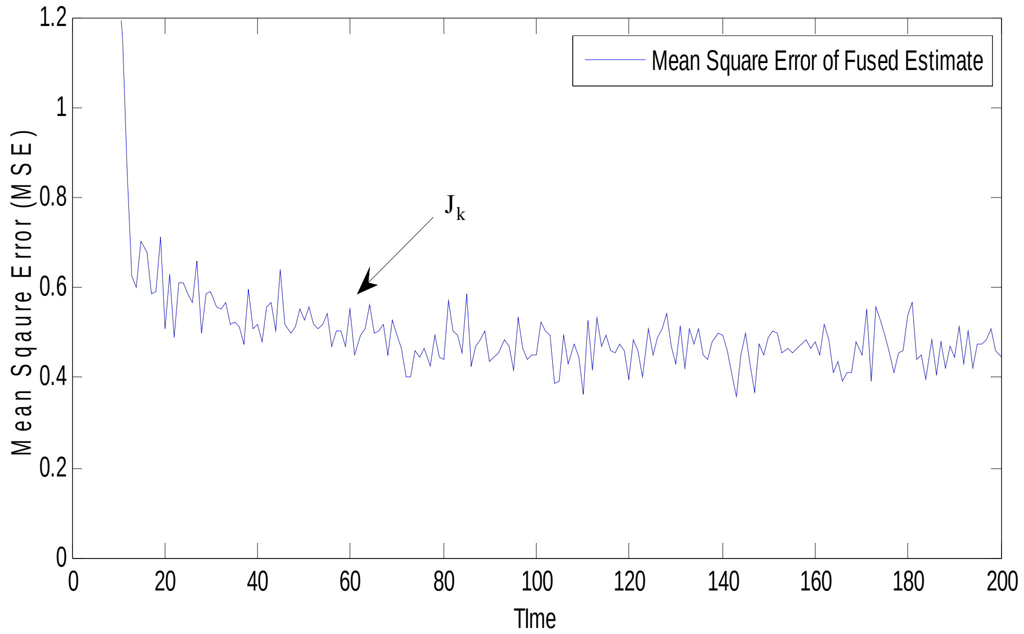

Figure 7. Mean Square Error of Fused Estimate $\hat{T}_{s,k}$

Mean square error of fused estimate is calculated from $J_k = E\left[(T_{s,k} - \hat{T}_{s,k})^2\right]$.

In Figure 7, $J_k \approx 0.2$ at k > 80, It means that global estimate $\hat{T}_{s,k}$ is within $\left(T_{s,k} \pm \sqrt{J_k}\right)$. The result shows that our proposed filter gives reasonably good accuracy.

5. CONCLUSIONS

Building a smart highway system requires a wealth of data, such as traffic flows, traffic control, accidental circumstances, road conditions, and weather. In this regard, a large-scale sensor network provides an optimal solution, since they are designed to meet these demands.

In this paper, new hierarchical fusion architecture for an arbitrary topology of large-scale sensor networks is proposed. The advantage of this hierarchical architecture is that it lessens the computation complexity of the decentralized data fusion algorithm [10]. In sensor networks, including computation complexity problems, link failure between the nodes and the cluster heads is also a problem needing to be solved [11].Thus, CI is applied to overcome the effect of redundant information.

In large-scale sensor networks, numerous sensors are used to measure the road surface temperature. However, it is probable that some sensors experience disorders that prevent them from obtaining temperature data. In this case, it is necessary to isolate these sensors and to properly calculate the global fuse estimate of the surface temperature. Thus, the LKF is applied to detect and isolate faulty sensors [8], [9].

In the simulation, the dynamic pavement surface temperature system (18) is adopted to apply and test the proposed algorithm for performance accuracy. The results show that the proposed algorithm is robust to measurement uncertainty and link failure between nodes and cluster heads.

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